Model-Based Fault Diagnosis in Electric Drive Inverters Using Artificial Neural Network

M. Abul Masrur, Senior Member, IEEE, ZhiHang Chen, Baifang Zhang, Hongbin Jia, and Yi Lu Murphey, Senior Member, IEEE

Abstract--**This paper presents research in model based fault diagnostics for the power electronics inverter based induction motor drives. A normal model and various faulted models of the inverter-motor combination were developed, and voltages and current signals were generated from those models to train an artificial neural network for fault diagnosis. Instead of simple open-loop circuits, our research focuses on closed loop circuits. Our simulation experiments show that this model-based fault diagnostic approach is effective in detecting single switch open-circuit faults as well as post-short-circuit conditions occurring in power electronics inverter based electrical drives.**

Index Terms-- **model-based diagnostics, power electronics, inverter, motor, electric drives, neural network, electric vehicle, hybrid vehicle, field oriented control.**

I. INTRODUCTION

A large number of electric vehicles (EV) and hybrid electric vehicles (HEV) [1] consist of 3-phase induction motor drives and associated power electronics based inverter, together with the necessary control system [1]. The precise torque control of these motors has been made possible by power electronics with controllable solid state switches, along with the Field Oriented Control (FOC) techniques [2-5]. However, the solid state switches can fail by being "open" or "shorted", and the reverse diodes in the switches can fail as well. This paper presents our research on the detection of open and post short-circuit faults in inverter switches.

There exists a good amount of work in the literature [6-7] on fault diagnostics of internal combustion (IC) engine vehicles. However, for electric or hybrid vehicles, fault diagnostic techniques are not yet well investigated, since EV/HEV is still in the infant stage in the automotive industry compared to IC engine vehicles. A closely related work by Ribeiro, Jacobina and Silva [8], was based on the direct comparison of voltages measured at a few key points of the system with application to an electric drive with open loop control. Our work extends the state of the art and uses a model that simulates a closed loop field oriented control electric drive, and generates multiple quantitative attributes of various signals including the torque, voltages and currents in all phases, for the diagnostic study.

Specifically, our research attempts to solve the following problem: "For a 6-switch inverter driven 3-phase induction motor under closed-loop control, given two current sensors in the output inverter lines, and two voltage sensors across the lines, identify the faulty inverter switch among the six switches, assuming the switch has a fault, and that only one out of six switches can fail at a time". A limited amount of literature on open loop control studies for fault diagnostics are available. However, little work has been conducted on closed loop situations yet, according to the published literature. Closed loop scenario is quite different from open loop. It can either be destructive to the closed loop system to induce faults using laboratory means, or the system can be shut off by a protective mechanism. The authors believe that simulated studies are important means to study the closed-loop problem followed by the laboratory validation in controlled environment. The authors are currently working towards the development of safe laboratory experiments and intend to report the same in their future publications.

We have developed a model of the inverter and a 3-phase induction motor along with its control mechanism that simulates the normal operations of the power electronics inverter as well as all single switch faults and three post-short-circuit conditions (defined later) within the 3-phase induction motor drive. The reason why we focus on the single switch failures is that they have a higher probability of occurrence than multiple switch failures. The model was implemented using the Matlab-Simulink software. Three important signals, namely the torque, and the voltages and currents in different phases, were used for the fault diagnostics. These signals were segmented and diagnostic features were extracted from signal segments. A multiple class neural network was then trained on these features. In a companion paper [9], the authors have developed and described in detail a systematic framework for choosing operating points of the drive for neural network training. This work, therefore, will not delve on those issues. Our results here will show that the neural network system trained on these models is effective in detecting the existence of single switch faults and accurately locating these faults in an open circuit as well as a post-short-circuit fault.

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and table II (for one switch open condition). In these tables, the symbol V_{an} (V_{bn}, V_{cn}) means voltage between line "A"("B", "C") and the neutral point "n" of the Y-connected stator winding of the induction motor.

TABLE I: SWITCHING TABLE FOR NORMAL OPERATION OF THE SWITCHES

STATE #	SWITCH A	SWITCH B	SWITCH C	Van / V	Vbn / V	Vcn / V
Null	0	0	0	0	0	0
1	0	1	0	-1/3	2/3	-1/3
2	0	1	1	-2/3	1/3	1/3
3	0	0	1	-1/3	-1/3	2/3
4	1	0	1	1/3	-2/3	1/3
5	1	0	0	2/3	-1/3	-1/3
6	1	1	0	1/3	1/3	-2/3
Null	1	1	1	0	0	0

Six faulty models are generated next, each of which simulates one switch open-faulted condition. Table II shows the truth table to simulate the switch A (see Figure 2) in open condition. Table II is based on the fact that when switch A (upper limb) is turned on, in reality it remains off.

TABLE II: SWITCHING TABLE FOR THE FAULTED OPERATION IN WHICH SWITCH A IS OPEN PERMANENTLY

STATE #	SWITCH A	SWITCH B	SWITCH C	Van / V	Vbn / V	Vcn / V
Null	0	0	0	0	0	0
1	0	1	0	-1/3	2/3	-1/3
2	0	1	1	-2/3	1/3	1/3
3	0	0	1	-1/3	-1/3	2/3
4	0 (supposed to be closed normally)	0	1	0	-1/2	1/2
5	0 (supposed to be closed normally)	0	0	0	0	0
6	0 (supposed to be closed normally)	1	0	0	1/2	-1/2
Null	0 (supposed to be closed normally)	1	1	0	0	0

For post short-circuit condition i.e. after complete burn out of a switch (with both the upper and lower switches in a particular limb open), in order to perform the simulation the dynamic equations of the three phase machine has to be restructured, with the corresponding phase current set to zero. It should be noted that when a particular phase current of the machine remains totally zero all the time, it is not possible to create a table in the same manner as Table II, due to the fact that the particular limb is open with infinite impedance.

The normal and the six faulty models were implemented by using the sine triangle PWM with a closed-loop FOC. Table III shows the operating conditions used in the simulation of these models.

Table III: The operating conditions used in the sine-PWM-closed-loop model

Variable name	Description	Value
V_{DC}	DC voltage provided by battery	500V
PWM Carrier Frequency	Frequency of the sine wave	8 kHz
Speed	Fixed running speed of the motor	60, 300, 600, 900, 1800 rpm
Reference torque command	Mechanical torque desired from the motor	10, 50, 100, 200 Nm
Simulation time	Simulation Time	6.25s
Trigger Time	Time point to trigger the fault condition	0.25s
Sampling rate	Sampling rate to get the output data.	0.001s
Number of data points	Number of data points	6000

Figures 3 through 8 show the simulated torque and currents generated under normal condition and two faulty conditions in a sine-triangle PWM based inverter with closed-loop FOC of the induction motor. In Figure 3, the step function is the command

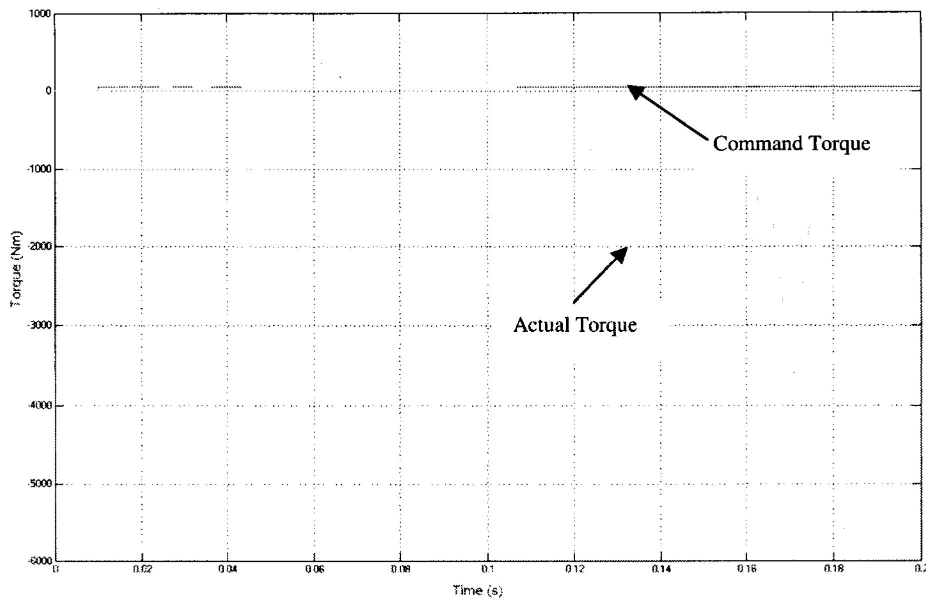

Figure 5. Torque signal with the switch A open condition in a sine-PWM-close-loop model.

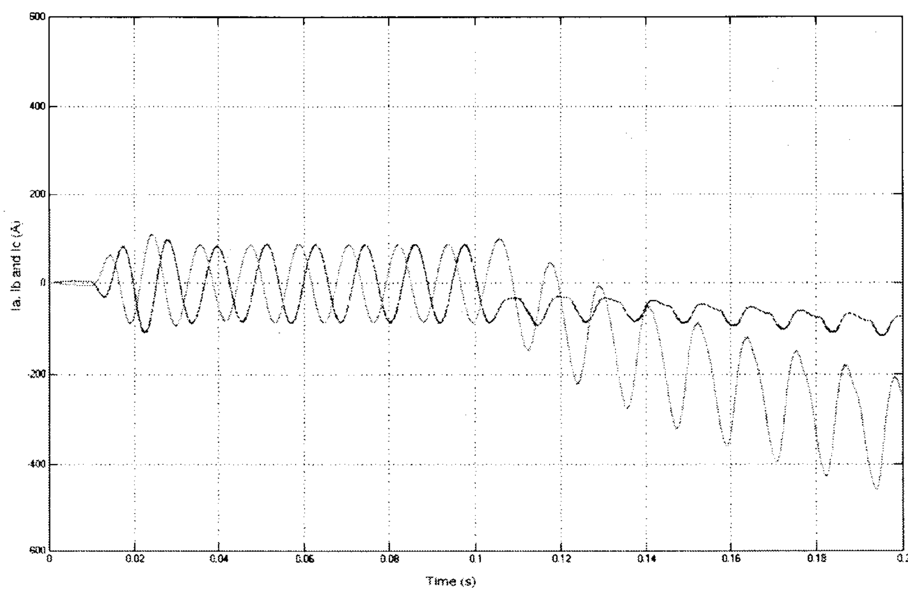

Figure 6. Ia, Ib, Ic signals signal with the switch A open circuited, using a sine-triangle PWM inverter with closed loop FOC control for the induction motor.

Figure 9 illustrates the computational steps involved in such a detection system. The input to the algorithm consists of the motor input voltages V_{an}, V_{bn}, V_{cn}, the currents I_a, I_b, I_c at the three phases in the inverter, and the motor electro-magnetic torque T_e (see Figure 1 and 2). The first two computational steps extract significant diagnostic features from input signals. A multi-class neural network is trained on signal features to decide whether the state of the electrical drive represented by input signal features are in the normal state or one of the faulty conditions.

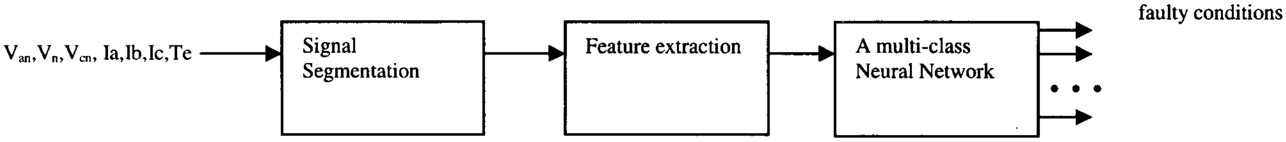

Fig. 9. Computational steps in a signal fault detection system.

A. Signal Segmentation and Feature Extraction

Fault detection is performed by analyzing the signal on a segment-by-segment basis. All input signals are segmented using the same fixed size and the two adjacent segments are overlapped by 1/3 of the segment in order to maintain continuity of information flow between segments. The basic frequency of the signals generated by the simulation models is little over 80 Hz and the sampling frequency is chosen to be 1000 Hz. We chose to use 16 samples in each segment, which corresponds to the signals within 1 ms. Two adjacent segments are overlapped with 5 samples. For a signal with 3000 data points, it is segmented into 272 segments, which include the overlapping zones. Figure 10 illustrates the segmentation scheme. Each blue

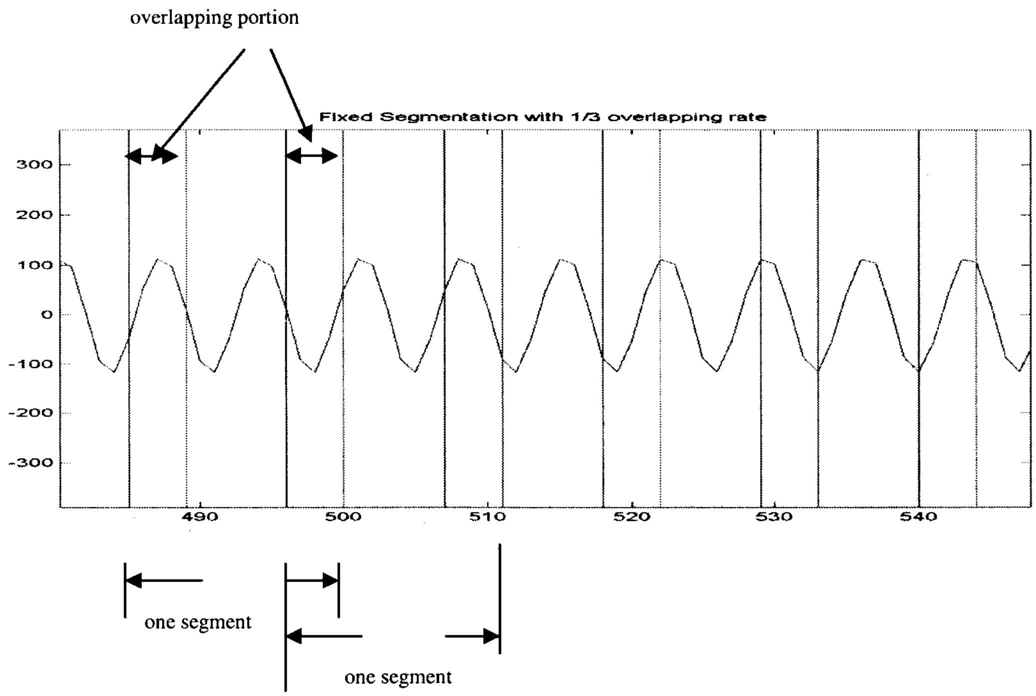

Figure 10. Segments on a signal

line indicates the beginning of a segment, and the first subsequent red line indicates the ending of the previous segment and the second one indicates the ending of the present segment. The signal between a blue line and the subsequent red line is the overlapping portion between the two adjacent segments. Each signal segment is represented by the following statistic features:

Max: maximum magnitude of the signal within the segment of the present segment.
Min: minimum magnitude of the signal within the segment.
Median: median of the signal within the segment.
Mean: mean of the signal within the segment.
Standard deviation: standard deviation of the signal segment.
Zero-frequency component of the power spectrum.

symbols, and tested on all the points shown in the pink squares and red triangles in Figure 12. The neural network performed with 100% accuracy on all the signals generated at the blue and pink points. A signal is considered 100% correctly classified by

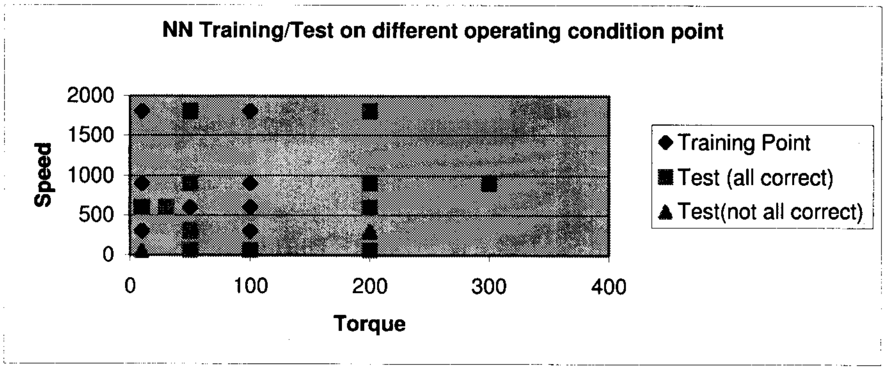

Figure 12. Operation points used to generate training and test data for diagnostics with 1-switch open.

the neural network, if all the "normal" segments on the signal are detected by the neural network as "normal", and all the "faulty" segments on the same signal are detected as the "faulty" class that matches the faulty condition used in data generation. Figure 12 showed that the neural network did not reach 100% accuracy on the test data generated at two particular operating points, (Torque=10, Speed=60) and (Torque=200, Speed=300). The performances of the neural network at these two operating points are shown in Table IV and V. In the first case, the system performed very well on all classes except the normal class. In the second case, the system gives above 90% accuracy on all classes except the class of faulty condition 6.

Table IV. Blind Test result at parameter points Torque =10 Speed =60

Condition	Correct Rate (%)
Normal	73.90
Fault 1	98.16
Fault 2	97.79
Fault 3	98.53
Fault 4	100
Fault 5	100
Fault 6	100
Total	95.48

Table V. Blind test result at parameter points Torque =200 Speed =300

Condition	Correct Rate (%)
Normal	100
Fault 1	91.18
Fault 2	94.49
Fault 3	100
Fault 4	100
Fault 5	100
Fault 6	74.26
Total	94.28

D. Fault detection of short-circuits

The second experiment was conducted to detect the post-short-circuit faults (Figs. 7, 8) in the six-switch inverter scheme shown in Figure 2. Three faulty classes were simulated, and each class was generated by making one vertical switch pair open at a time, namely, the pairs A and A', B and B', and C and C' respectively (see Figure 2). We used a neural network architecture of 42 input nodes, 1 hidden layer with 20 nodes, and 4 output nodes representing the normal class and the 3 faulted classes.

The neural network was trained on the data generated at the 8 operating points shown in the blue diamond symbols, and was tested on all the points shown in Figure 13, where the pink squares and red triangles represent the operating points at which the test data were generated. The neural network performed with 100% accuracy on all the signals generated at the blue and pink points. Figure 13 also showed that the neural network did not reach accuracy of 100% (but greater than 90%) on the test data generated at two operating points (Torque=10, Speed=60) and (Torque=50, Speed=60). The performances of the neural network at these two operating points are shown in Table VI and VII. The neural network performed quite well on all classes.

These experiments show that the artificial neural network trained by the data generated from the normal and faulty models has the capability of detecting the faults over a very large portion of the torque-speed domain with very high degree of accuracy. We notice that only at two points of very low speeds the neural networks did not achieve 100% accuracy: the results' prediction rates were around 75% for the single switch open-circuit fault, and above 90% for the post-short-circuit fault. We are investigating a machine learning algorithm that can select more representative operating points for training more robust neural networks for all points in the speed-torque domain.

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VI. BIOGRAPHIES

M. Abul Masrur (M'84, SM' 93) received the Ph.D. in Electrical Engineering from the Texas A & M University, College Station, Texas, USA in 1984. He was with the Scientific Research Labs. of the Ford Motor Co. from 1984 to 2001 and was involved in research and development related to simulation and control for electric drives for electric and hybrid electric vehicles (EV & HEV) and power electronics, advanced automotive electric energy management and vehicular power system architecture, automotive multiplexing systems, and related works. Dr. Masrur joined the US Army RDECOM-TARDEC in its Vetronics Technology Department in 2001, and is involved in various vehicular electric power system architecture concept design and development for military applications. He has over 40 publications, and 6 US patents. He received the Best Automotive Electronics Paper Award from the IEEE Vehicular Technology Society, USA, in 1998. Dr. Masrur is a Senior Member of the IEEE and since 1999 he has been serving as an Associate Editor of the IEEE Transactions on Vehicular Technology.

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